Applied Financial Economics, 2002, **12**, 431–445

Product mix clubs, divergence and inequality of Spanish banking firms

FRANCISCO PÉREZ and EMILI TORTOSA-AUSINA*‡

Departament d'Anàlisi Econòmica and IVIE, Universitat de València, Campus dels Tarongers, Edifici Departamental Oriental, 46011 València, Spain and ‡ *Departament d'Economia, Universitat Jaume I, Campus del Riu Sec, 12071 Castelló de la Plana, Spain.*

The expansion and intensification of banking competition, undergone by the Spanish banking industry during the last 15 years, has allowed commercial banks and savings banks to more freely define their competitive strategies. This paper reports empirical evidence on the similarities and differences in banks' product mixes along with their time evolution. In particular, it attempts to identify the different kinds of firms according to their output mixes and, on this basis, to analyse if the deregulation and increased competition have resulted into the homogenization (convergence) of specializations between firms or groups of firms (clubs). The empirical success is higher when product mix clubs are considered, achieving higher heterogeneity within the banking system as a whole but increased homogeneity within certain clusters of commercial banks and savings banks.

I. INTRODUCTION

Over the last 15 years, many European countries have witnessed a strong and ongoing shift in the conditions surrounding their banking industry. Deregulation, technological change, removal of entry barriers and internationalization of the economies are some of the outstanding features of such transformations, all of which markedly affected banking firms, which have been impelled to modify their competitive strategies in a wider context for products and markets. In these circumstances, one of the most important components of such strategies turns out to be the choice of a certain specialization in their production lines.

Indeed, due to deregulation and increased competition in the banking industry, it might be argued that the differences between banks' product mixes will tend to increase. This could be particularly the case in the Spanish banking system, as a broad group of firms (savings banks) had restrictions to both their geographic expansion and engaging into some activities. Such restrictions could, obviously, affect firms' output mixes, and if they were removed firms could more freely define the products and services in which to specialize.

In addition, many studies do explicitly consider that those factors contributing to reshape the European banking industry have somewhat affected balance sheet characteristics of banking firms and, consequently, firms' output mixes. However, conclusions used to be drawn only at industry level or, at most, considering some type of firms aggregate.[1] In such a case, although prior achievements are undoubtedly interesting, they do not capture all the differences that could underlie at firm level and which might be hidden by aggregate data.

The relevance of considering firms' output mixes comes also from their influence on cost structures. This has been fully addressed in Kolari and Zardkoohi (1987, 1995) relative to a sample of US banks and Gual and Hernández (1991) relative to a sample of Spanish savings banks. Maudos *et al.* (2000) consider additionally that banks' output mixes bias cost efficiency scores in a way such that a

* Corresponding author. E-mail:tortosa@uji.es

[1] This approach is usual when different types of institutions exist. In the Spanish banking industry it is common practice analysing the trends for commercial banks and savings banks separately.

Applied Financial Economics ISSN 0960–3107 print/ISSN 1466–4305 online © 2002 Taylor & Francis Ltd
http://www.tandf.co.uk/journals
DOI: 10.1080/0960310001000111 7

firm could be mislabelled as inefficient only because of the (more expensive) products and services in which it specializes. This point has been also forcefully made in Tortosa-Ausina (1999a, 1999b). The overall conclusions show that, indeed, firms' specializations should be controlled for when analysing cost issues.

Bearing in mind the importance of the above reasonings, the purpose of this paper is to identify the lines of specialization of banking firms in this reshaped environment, along with their evolution throughout time and their influence on firms' costs levels. The analysis is accomplished through a database of Spanish banking firms; however, the interest of the exercise tries to capture also the usefulness of applying some of the frequently used techniques in the economic growth and inequality literature to the study of the specialization of multiproduct firms.

The approach used in this paper to assess the specialization and its time evolution in the banking industry has been partly considered in different studies.[2] With similar attempts to those pursued in this paper, Pastor and Pérez (1999) analyse the differences in the product mix patterns between commercial banks and savings banks considering each type of institution aggregate as the representative firm. Their study provides an overview of the shifts faced by banking companies' balance sheet structures over the period 1985–1996, finding that there is a tendency of both types of institutions to narrow or widen their product mixes – depending on the analysed item – throughout their sample period, in which the increased competition has allowed firms to choose less regulation-conditioned competitive strategies. The overall conclusion is that, although convergence appears to exist in some balance sheet items, no clear pattern holds for most of them.

However, it is not possible from such a study to achieve a conclusion as to whether the widening of markets and products has resulted in increased homogeneity (or diversity) within the banking sector or not. First, results tend to be somewhat ambiguous. Second, as stated above, competitive strategies must be studied considering the individual firm, rather than any type of institution aggregate. For that reason, in our study possibilities to develop an analysis of the addressed problem related to the banking firms are exploited.

Furthermore, when trying to study banking firms, both statistical and instrumental difficulties emerge. The former refer to the available data at the firm-level,[3] which do not provide the same degree of detail as the aggregate data,[4] forcing us to use slightly different product mix indicators. The latter is more substantial, as it deals with the way of designing product mix indicators which summarize the behaviour of multiple firms and multiple product lines.

The paper is structured as follows. Section II defines the product mix indicators to be analysed in Section III from both a static and dynamic point of view. Section IV considers whether any type of clustering of firms might influence results on output mix dynamics at industry level, while Section V assesses jointly results of Sections III and IV by means of a different technique, and gives rise to Section VI, which assesses the influence of firms' output mixes on both financial and operating costs. Finally Section VII concludes.

II. BASIC PRODUCT MIX INDICATORS

In order to analyse the banking product mix, a measurement of banking output is required. This question has often been involved in debate and controversy.[5] According to our attempts, it is necessary to use an output measure which allows us to identify product diversity. This is the reason underlying the use of balance sheet items as output indicators, although this choice has well known shortcomings.[6]

Thus, the starting point consists of defining some basic product mix indicators derived from the chosen output measures. Let X_{ij} be firm j's balance sheet's item i, $i = 1, \ldots, I$ (number of firms) and $j = 1, \ldots, J$ (number of items). When the items are asset items, they will be denoted by A_{ij}, and L_{ij} when they are liability items. Let $X_j = A_j, L_j$ be the aggregate value of item i for all firms.

According to this, the output of a firm is defined by its assets and liabilities vector

$$X_j(A_{ij}, L_{ij}) \tag{1}$$

and the vectors of the firms as a whole make up a matrix

$$X(X_j) = X(A_{ij}, L_{ij}) \tag{2}$$

This type of matrix, including firms' output in its rows, is available at every period. Similarly, we have two aggregate vectors: each firm's aggregate vector (X_j) and each product aggregate vector (X_i).

Finally, the basic group of product mix indicators is obtained by mean of

$$x_{ij} = \frac{X_{ij}}{X_j} \tag{3}$$

[2] See, among others, Freixas (1996), Gual and Hernández (1991) or Sánchez and Sastre (1995), relative to the Spanish banking industry.
[3] These are published by the Spanish Banking Association (AEB) and the Spanish Confederation of Savings Banks (CECA).
[4] Published by the Bank of Spain. This institution, however, does not provide data at firm-level.
[5] See, for instance, Berger and Humphrey (1992).
[6] However, some of such shortcomings, like the increasing importance of the off-balance sheet operations, have not been fully exploited by the literature of Spanish banking firms.

which constitute a matrix made up of the elements defined in such a way. Its main advantage consists of every firm's row being comparable with the others, as the production scale effects have been removed (Equation 3). Each column i represents the intensity of the specialization of the different firms in product i.

Finally, the set of available data matrices x_{ij} is conditioned only by the existing observations in the analysed period t. For these purposes, five balance sheet items (columns) – five items on the assets side and four items on the liabilities side —, 121 firms[7] (rows) and 12 years (matrices) are employed.

III. PRODUCT MIX MEASURES

Considering the x_{ij} indicators as a starting point, it is possible to analyse the product mix from two different approaches: from the homogeneity or heterogeneity between firms, and from the time evolution.

Homogeneity in specialization

Consider now, any of the column vectors in the matrix $x(x_{ij})$. Each of the elements of the vector i has a value ranging from zero to one and reveals the intensity of the specialization in every product line. A homogeneous or heterogeneous product mix measure at any point in time for each balance sheet item will be given by the density function dispersion measures made up of the available observations: either the variation coefficient (ρ) or the standard deviation (σ) (depending on whether we want to control for the shifts in the mean values of x_{ij} or not).

The lowest values in the dispersion measures of the specialization coefficients would show banking firms being more homogeneous between them in the considered product line. Relative to the variation coefficients, as they have been divided by the mean, we are able to identify the items where the relative homogeneity between firms is highest, regardless of their importance in the balance sheet.

Table 1 shows the variation coefficients' values corresponding to the most important assets and liabilities items[8] for every year in our sample. Table 2 shows them in a decreasing order but only for the initial and final years, in an attempt to more clearly appreciate that equity holdings, issued securities, interbank deposits and other deposits show the highest relative dispersion; similarly, comparing 1985 and 1996 data, it is possible to notice that dispersion has declined in some cases, but has increased in others, there being no *a priori* evident pattern towards homogeneity or diversity of product mixes. It must be realized, though, that the importance in the balance sheet of each item being considered varies much, as Table 3 shows.

Evolution of specialization: do tendencies exist?

Table 1 leads us in a natural way to wonder whether a steady tendency towards the homogeneity of product mixes exists or not. In order to identify such at tendency, the time evolution of x_{ij} items variation coefficients' values, known as σ-convergence,[9] has been plotted (Figs. 1 and 2).

Table 1. *Convergence in specialization* (*relative dispersion*), *banking firms* (*1985–1996*)

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
Assets												
Cash and Bank of Spain	0.48	0.52	0.45	0.47	0.48	0.62	0.72	0.50	0.55	0.56	0.57	0.63
Fixed-income securities	0.37	0.36	0.40	0.41	0.48	0.47	0.45	0.59	0.62	0.60	0.67	0.63
Interbank loans	0.84	0.72	0.94	0.94	0.89	0.80	0.83	0.72	0.62	0.68	0.68	0.78
Credit to firms and households	0.36	0.35	0.36	0.37	0.39	0.39	0.40	0.39	0.41	0.41	0.44	0.46
Equity holdings	1.55	1.91	1.33	2.83	2.21	2.26	2.21	2.64	2.95	3.12	2.77	3.11
Liabilities												
Savings deposits	0.53	0.53	0.55	0.52	0.52	0.50	0.48	0.44	0.44	0.43	0.45	0.50
Other deposits	0.73	0.79	0.84	0.85	0.74	0.74	0.81	0.88	1.00	1.04	1.05	1.00
Interbank deposits	1.47	1.61	1.70	1.52	1.55	1.51	1.25	0.99	1.29	1.29	1.13	1.21
Issued securities	2.02	2.02	2.24	2.75	3.36	4.03	3.70	3.26	3.48	3.51	2.91	3.34

[7] Some firms were dropped from the original sample for two reasons. First, as the analysed period has witnessed a remarkable number of mergers and acquisitions, firms engaged in such a process were backwards added, despite the (known) shortcomings of such an approach. Second, as interest is primarily in the convergence process – which requires considering the same firms for the 12 years – all those firms starting or ending up their activities during the regarded period were dropped. Although this could seem an important loss of data, the sample always involves roughly 90% of total assets.

[8] In the overwhelming majority of cases, they jointly represent around 90% of all assets.

[9] This representation has become standard in the empirical literature on economic growth in the 1990s since the Barro and Sala-i-Martin (1992) study, where the concept of σ-convergence is defined.

Table 2. *Convergence in specialization (relative dispersion), banking firms (1985 vs 1996)*

1985		1996	
Issued securities	2.02	Issued securities	3.34
Equity holdings	1.55	Equity holdings	3.11
Interbank deposits	1.47	Interbank deposits	1.21
Interbank loans	0.84	Other deposits	1.00
Other deposits	0.73	Interbank loans	0.78
Savings deposits	0.53	Fixed-income securities	0.63
Cash and Bank of Spain	0.48	Cash and Bank of Spain	0.63
Fixed-income securities	0.37	Savings deposits	0.50
Credit to firms and households	0.36	Credit to firms and households	0.46

Its decreasing evolution would indicate firms *converging* in the intensity of their specialization in the item being analysed, whereas divergence occurred in the opposite case.

Figure 1 shows the results for four analysed assets items,[10] while Fig. 2 represents its counterpart for the liability side. From its visual analysis it is noticeable that a clear tendency towards convergence in interbank loans emerges but, on the other hand, fixed-income securities, other deposits, issued securities, equity holdings and even (although to a lesser extent) credit to firms and households show the opposite pattern (divergence).

Another way to consider the shifts in output mixed deals with analysing if the intensity of the specialization at the initial moment affects the specialization variation rate throughout the sample period. Thus, if the fact of a firm being more oriented towards a certain specialization leads it to experience smaller intensifications of such a specialization in the future and, on the other hand, if the initially less specialized firms grow faster in that way, we will notice an inverse relationship between the initial level $x_{ij,0}$ and the variation rate of such a measure. This pattern is known as β-convergence[11] and leads to closer final x_{ij} values, so we will test differently how product mixes converge.

In order to quantify if β-convergence exists, we must estimate for all the items the equation

$$\frac{1}{T}\log\frac{x_{i,jt}}{x_{ij,t-T}} = a - \beta\log(x_{ij,t-T}) + u_{ij,t-T} \qquad (4)$$

where T represents the length of the sample period and $u_{ij,t-T}$ the error term.

Table 4 shows least squares estimates for Equation 4 using least squares estimation for all product lines and firms in our sample. Results help assessing the overall sign of the tendency throughout the period. However, they do not allow us to notice the shocks which have taken place within the period, as only the initial and final years are being considered.[12] The value of the estimated β shows us the rate at which banking firms converge or diverge in a certain specialization.

Excluding the credit to firms and households and issued securities case, in which coefficients are not significant at usual levels, we notice convergence in all product lines, although the fitness of the regression (R^2) is somewhat poor in some cases, and the β values differ across items.[13]

Table 3. *Balance sheet structure for selected items, banking firms (1985–1996)*

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
Assets												
Cash and Bank of Spain	10.38	10.27	12.06	10.31	10.58	3.28	3.94	2.24	1.72	1.78	1.55	1.45
Fixed-income securities	22.08	24.17	21.53	21.32	19.71	24.46	20.60	17.84	14.53	16.84	17.19	16.07
Interbank loans	20.44	18.88	18.50	17.36	20.62	21.00	20.96	25.20	32.12	29.47	30.56	30.64
Credit to firms and households	37.08	37.33	39.20	41.64	39.77	41.57	45.11	45.66	43.07	43.14	42.43	43.62
Equity holdings	1.29	1.53	1.30	2.44	2.35	2.68	2.26	2.12	2.30	2.35	2.03	2.50
Liabilities												
Savings deposits	48.94	50.70	50.12	51.03	48.70	49.46	50.97	54.21	55.74	56.28	54.07	52.02
Other deposits	24.38	19.85	20.19	19.70	22.22	19.77	18.80	11.43	11.35	11.49	13.41	13.78
Interbank deposits	9.56	11.18	10.36	9.35	9.99	9.54	12.39	16.48	14.81	15.75	14.19	15.47
Issued securities	4.55	5.25	4.74	4.34	2.06	1.58	1.40	1.33	1.20	0.96	0.78	0.76

Note: % of total assets.

[10] Equity holdings were not considered in a preliminary version of this paper and, as they involve (on average) less than 3% of total assets, have not been plotted; however, their increasing importance in the balance sheet of some firms suggested they should be introduced in the analysis too.

[11] Again, this approach to convergence was proposed by Barro and Sala-i-Martin (1992) and has been widely used in the study of convergence in *per capita* incomes.

[12] This point has been forcefully made in Tortosa-Ausina (1999b).

[13] It should be pointed out that the existence of β-convergence is fully compatible with a tendency of growing dispersion. Indeed, whereas σ-convergence implies β-convergence, the opposite does not hold (see Barro and Sala-i-Martin, 1992). Thus, results might not coincide for σ and β-convergence, as they are not exactly the same and refer to different facts. This question, and the relevance of studying β-convergence regardless of the evolution of any dispersion measure are fully addressed by Sala-i-Martin (1996).

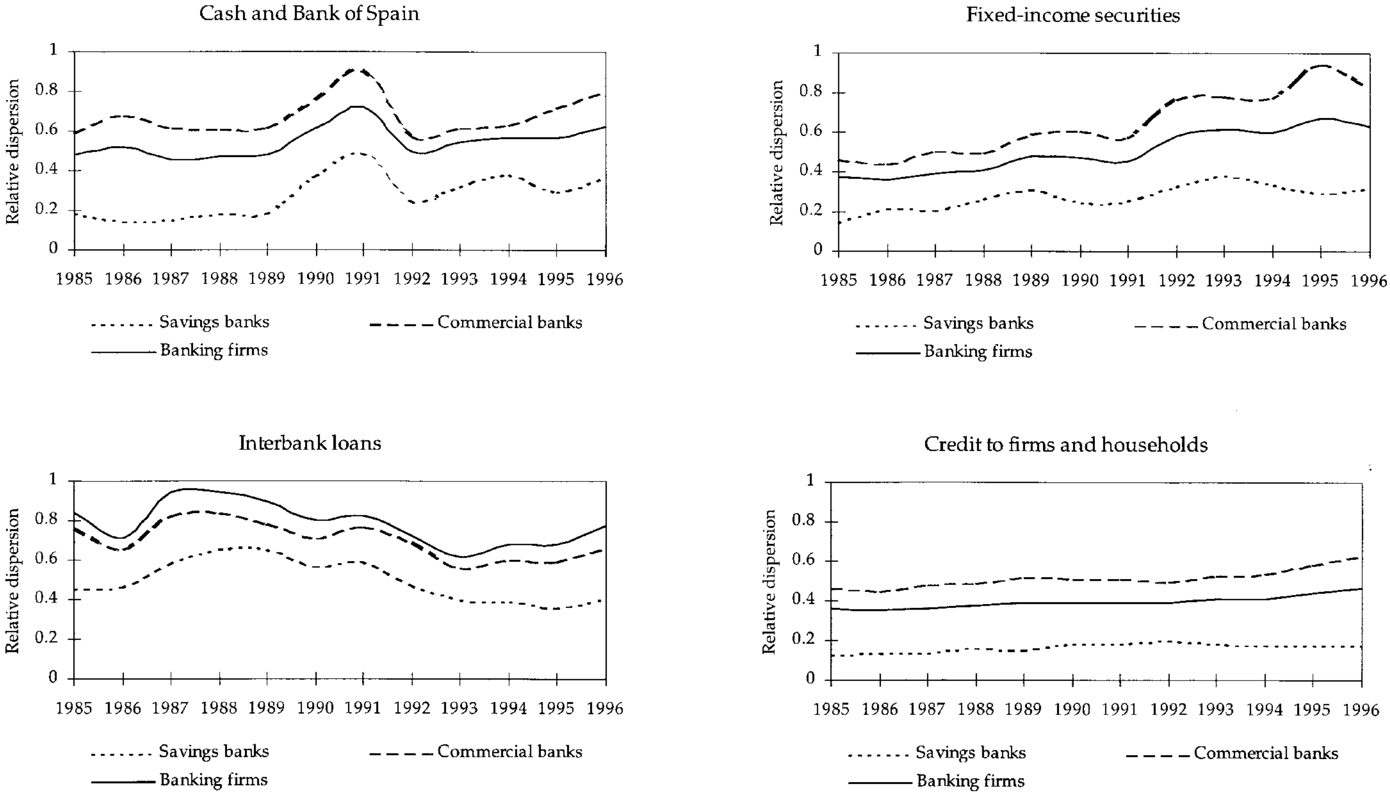

Fig. 1. *σ-convergence in specialization, banking firms (assets)*

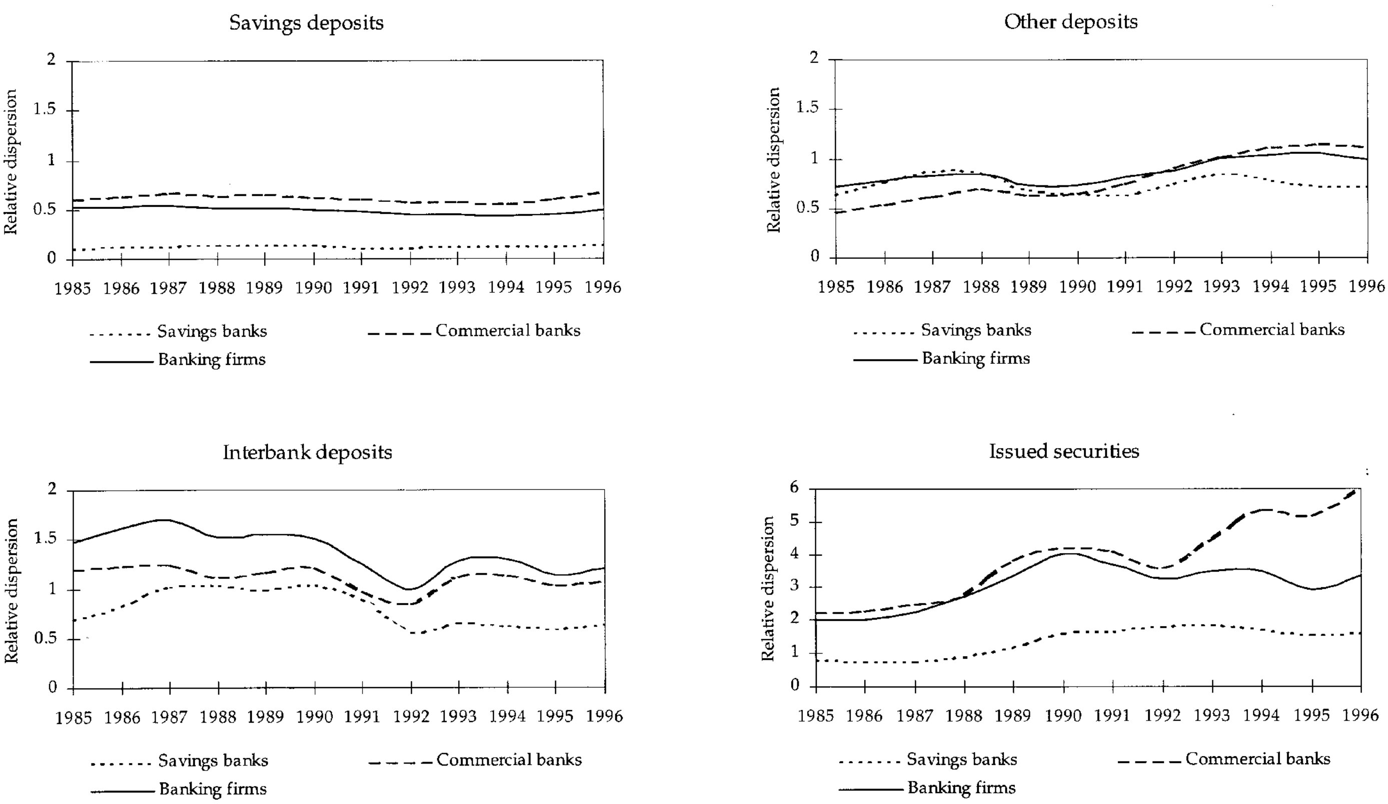

Fig. 2. *σ-convergence in specialization, banking firms (liabilities).*

Table 4. *Absolute convergence in specialization, banking firms (1985–1996)*

	Commercial banks and savings banks
Cash and Bank of Spain	
β	0.062
(t-statistic)	(5.720)
R^2	0.461
Fixed-income securities	
β	0.068
(t-statistic)	(4.289)
R^2	0.373
Interbank loans	
β	0.061
(t-statistic)	(5.226)
R^2	0.334
Credit to firms and households	
β	0.041
(t-statistic)	(1.567)
R^2	0.042
Equity holdings	
β	0.055
(t-statistic)	(6.961)
R^2	0.317
Savings deposits	
β	0.066
(t-statistic)	(8.866)
R^2	0.501
Other deposits	
β	0.064
(t-statistic)	(5.801)
R^2	0.249
Interbank deposits	
β	0.051
(t-statistic)	(6.918)
R^2	0.302
Issued securities	
β	0.032
(t-statistic)	(1.688)
R^2	0.063

Note: β values closer to zero suggest slower convergence.

Such values, which show the rate at which firms are getting closer in their specializations, suggest that the required time for the x_{ij} of the different firms relating to a certain column to be equalized is rather long. The rate is specially high and significant in the case of savings deposits. Although convergence exists also in other cases, either the significance or the coefficient values are not so high.

The overall conclusion of this analysis consists of a certain approach in the specializations of Spanish banking regarding β-convergence, although the speed differs substantially depending on the analysed item. These results are not confirmed when applying σ-convergence: in this case neither overall no clear patterns emerge. However, if we interpret these results as an absence of relationship in the banks' selected output mixes, the prediction would be at odds with the conventional wisdom of Spanish banks being increasingly sensitive to the other firms' product mixes. One plausible explanation could be that banking companies' concerns about other firms specializations were focused only on their most immediate rivals. In such a case, in order to appreciate convergence it becomes necessary to ponder in a different way the conduct of Spanish banking firms, trying to identify the groups of banks and savings banks which compete against each other.

IV. DO COMPETITION CLUBS EXIST?

One of the possible choices is that, indeed, as Kolari and Zardkoohi (1987) pointed out, banking firms should not be treated as one homogeneous group, as they use 'to cluster around specific market niches that are distinct from other markets'. Thus, it would be more interesting to study the evolution of the specialization between groups of competitors instead of all banks. The regarded hypotheses to identify rival groups are multiple, but we will consider the following:

- Type of institution: in this case, the hypothesis lies in the institutional difference between commercial banks and savings banks being significant for their specialization due to their historical trajectory, as they currently face the same regulatory environment.
- Size: we consider here large firms being rivals and imitating each other in their product mix. The same occurs with medium and small firms.
- The own product mix: in this case, the posed idea lies on firms' chosen specializations being the relevant issue to identify competitors and, therefore, to analyse the evolution of specialization.

The analysis in each of the different alternatives is focused as follows. First, depending on the selected criterion, groups on which the evolution of specialization is going to be analysed must be identified. Second, it is necessary to assess if cluster formation influences firms' convergence in specialization, both on its existence and its rate.

Regarding the formation of groups, and relative to the first hypothesis we made, the institutional difference between commercial banks and savings banks leads to an automatic clustering of firms. The size hypothesis impels us to decide upon the selected steps, choosing three categories. Finally, the chosen criterion to cluster firms by their product mix consists of identifying the specialization patterns from the x_{ij} indicators, and falling back on the cluster analysis multivariate statistical technique. By means of such an analysis it is possible to identify, through the application of a similarity or distance measure to the different x_{ij}, how close firms' specializations are. Once the distances have been computed, the following step consists of including in the same group (or cluster for firms) all those firms with an output mix similar to that of all other firms in their group but unlike those firms in all other groups.[14] The Ward's method, which minimizes the intra groups variance, has been chosen to form the analysed clusters.[15] From these criteria, and applying them to year 1996 data, seven groups were finally formed, although results are sometimes reported for only six of them, as the remaining group involves less than 1% of total assets in the industry.[16]

In contrast, it could be considered that deregulation has allowed institutions to shift their activities towards others different from the ones they had before. Consequently, groups might be alternatively formed from 1985 data, and in such a case the expected pattern could be firms undergoing shifts in their output mixes, making them increasingly different from the ones in their group, as their prior specialization could be markedly affected by regulation. This exercise has been also done, and the number of groups was (again) seven, but with a cluster membership substantially different from that achieved from the 1996 analysis.[17]

Once firms have been grouped according to the three described hypotheses, the σ and β convergence, analysis has been replicated for each of the resulting banks' clusters: two in the first hypothesis, three in the second and seven in the third (according both to groups in 1985 and 1996). Relative to σ-convergence, it is difficult to find general behaviour guidelines because of the heterogeneity in the results, as we got before. On the other hand, the β-convergence analysis contributes to better assess whether the specialization throughout the 1985–1996 period is influenced (conditioned) in its significance or rate by the selected clusters of banks. However, the β-convergence equation to be estimated now differs slightly from the one estimated above. In particular, its expression will be

$$\frac{1}{T}\log\frac{x_{ij,t}}{x_{ij,t-T}} = a - \beta\log(x_{ij,t-T}) + \phi z_{ij} + u_{ij,t-T} \qquad (5)$$

where z_{ij} is a vector of dummy variables which takes value one or zero, depending on the firm being member of a certain cluster or not.

The results of the estimation with the first clustering (commercial banks and savings banks) show a certain increase in the rate of convergence of some balance sheet items, although changes are not important (see Table 5, column 1). The second series of estimations, related to the clustering by size, show dimension as a little conditioning factor when analysing convergence in specialization, except for certain items (see Table 5, column 2). Finally, the third of the clustering hypotheses does noticeably affect the results when groups are identified according to firms' current specializations (see Table 5, column 4), leading to an important increase in the fitness of the regression (R^2) and β coefficients. According to 1985 grouping, however, such an improvement in the regressions does not hold (Table 4, column 3).

The way to interpret such results is the following: if banking firms are clustered by their product mix similarity, and their last decade trajectory is analysed, we verify that, *ceteris paribus*, each of the clusters will have converged to a very similar product mix in few years. In other words, if the current strategies in what specialization concerns are held, there will be groups of firms with almost homogeneous product bundles, depending on the level of detail that the available information permits.

V. WHERE IS THE BANKING SECTOR DIVERSITY?

According to what has been seen, when all banking firms are considered, the different firms' product mixes do not show a clear pattern either towards homogeneity or towards diversity. If an aggregate indicator of the σ-convergence indicators is designed, as a weighted mean of such indicators, a slight increase in heterogeneity is appreciated. This statement is justified by considering the weighted variation coefficient of the assets or liabilities

[14] This approach has been used in many other studies on banking product mix. See, for the Spanish case, Freixas (1996), Gual and Hernández (1991) or Sánchez and Sastre (1995). For the American case a sizeable literature exists, and the studies by Amel and Rhoades (1988) and Kolari and Zardkoohi (1987) are two good examples of it.

[15] The chosen similarity measure to compute the distances has been the squared Euclidean distance, defined as

$$d_{ij} = \sum_{k=1}^{p}(x_{ik} - x_{jk})^2 \qquad (8)$$

where x_{ik} and x_{jk} are the observations values i and j for the x variable, and p is the number of variables (ratios) which characterize each observation (enterprise).

[16] Details on group membership for the three hypothesis considered are available from the authors upon request.

[17] The cluster analysis was done for all years in the sample in order to form time stable clusters, but results were unsuccessful. However, one of the most remarkable features was that the appropriate number of groups at the initial years (according to their statistical properties) was much lower than at the final years. Some further discussion on this question appears in Appendix A.

Table 5. *Conditional convergence in specialization, banking firms* (*1985–1996*)

	Type of institution*	Size**	Product mix***	
			1985	1996
Cash and Bank of Spain				
β	0.072	0.062	0.072	0.093
(t-statistic)	(6.542)	(5.669)	(6.724)	(9.462)
R^2	0.526	0.463	0.534	0.757
Fixed-income securities				
β	0.081	0.068	0.093	0.093
(t-statistic)	(6.225)	(4.164)	(8.522)	(8.581)
R^2	0.479	0.384	0.553	0.698
Interbank loans				
β	0.074	0.062	0.077	0.076
(t-statistic)	(7.317)	(5.115)	(6.107)	(10.584)
R^2	0.417	0.339	0.432	0.519
Credit to firms and households				
β	0.049	0.044	0.046	0.105
(t-statistic)	(1.896)	(1.620)	(1.456)	(4.389)
R^2	0.124	0.048	0.046	0.625
Equity holdings				
β	0.056	0.061	0.061	0.060
(t-statistic)	(6.836)	(7.348)	(6.291)	(6.945)
R^2	0.360	0.353	0.395	0.412
Savings deposits				
β	0.076	0.066	0.072	0.104
(t-statistic)	(10.686)	(8.836)	(10.920)	(12.444)
R^2	0.542	0.501	0.599	0.710
Other deposits				
β	0.037	0.064	0.060	0.057
(t-statistic)	(3.088)	(5.950)	(4.360)	(5.768)
R^2	0.331	0.286	0.295	0.469
Interbank deposits				
β	0.060	0.056	0.068	0.076
(t-statistic)	(6.816)	(7.233)	(8.108)	(13.589)
R^2	0.336	0.327	0.387	0.586
Issued securities				
β	0.026	0.022	0.057	0.046
(t-statistic)	(1.445)	(0.959)	(2.136)	(2.581)
R^2	0.178	0.107	0.262	0.605

Notes: * includes type of institution dummies; ** includes size dummies; *** includes product mix dummies for groups based upon 1985 and 1996 data.

specialization indicators, or the whole balance sheet, computed in the following way

$$\rho_\omega = \sum_{i=1}^{n} \frac{X_i}{\sum_{i=1}^{p} X_i} \rho_i \tag{6}$$

where ρ_i, $i = 1 \dots n$, represents the standard deviation of each of the variables considered in the balance sheet analysis, $n = 5, 4, 9$ (depending on whether the assets side is analysed, the liabilities side or the total balance sheet) and $p = 5, 4$ (depending on the i item being an asset item or a liability item).

Figure 3 shows an increase of the dispersion in the assets side of the balance sheet, although the same does not hold for the liabilities side. In the same way, dispersion is always higher, and increasing throughout time when the whole balance sheet is considered.

Despite of all this, if the observed tendency to homogeneity in the conduct of the Spanish banking firms when the convergence between the members of a product mix club is considered, one might wonder whether a simultaneous increase in the diversity between groups could be undergoing along with a decline of such a diversity within groups.

In order to ponder such a question, one might initially contemplate the same aggregate indicator for the product

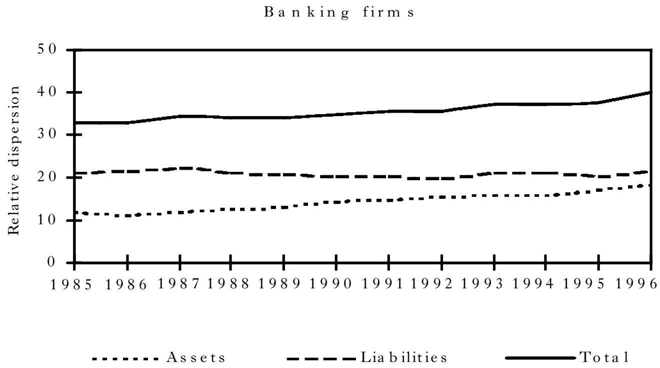

Fig. 3. *Convergence in specialization, total balance sheet* (*banking firms*)

mix evolution, but computing it for each of the seven[18] identified groups. Results are, according to Fig.4, very different from the presented in Fig. 3. First, one observes that convergence in the whole balance sheet exists for the overwhelming majority of groups, specially during the 1990s. Second, a clear tendency towards convergence in the liabilities specialization in all the reported groups is achieved, whereas no steady tendency is observed for the assets.

Thus, results vary depending on the clustering of firms. According to this, it is interesting to analyse their joint meaning, along with their compatibility. With this purpose, we might employ a broadly used instrument in the inequality studies: the Theil index. Such an index has the appealing feature of allowing a decomposition of the total inequality in terms of the observed inequality between different data groupings.

This attempt is to differentiate the contribution to the total inequality evolution of the differences between groups and within groups. The Theil index is computed according to the expression

$$TI_j = \sum_{k=1}^{K} x_{jk} \log \frac{x_{jk}}{y_k} + \sum_{k=1}^{K} x_{jk} \sum_{i=1}^{I} \frac{x_{ijk}}{x_{jk}} \log \frac{\frac{x_{ijk}}{x_{jk}}}{\frac{y_{ik}}{y_k}} \tag{7}$$

where

TI_j: total inequality j item

$i = 1, \ldots, I$: firm's subscript

$j = 1, \ldots, J$: item's subscript

$k = 1, \ldots, K$: cluster's subscript

I : number of firms in each cluster

K: number of clusters being considered

$$x_{jk} = \frac{\text{total item } j \text{ amount of the } k\text{th cluster}}{\text{total item } j \text{ amount of all } K \text{ clusters}}$$

$$y_k = \frac{\text{total assets of the } k\text{th cluster}}{\text{total assets of all } K \text{ clusters}}$$

$$x_{ijk} = \frac{\text{total item } j \text{ of the } i\text{th firm affiliated to cluster } k}{\text{total item } j \text{ amount of } k\text{th cluster}}$$

$$y_{ik} = \frac{\text{total assets of the } i\text{th firm}}{\text{total assets of all } K \text{ clusters}}$$

The first term on the right represents the between groups inequality contribution to total inequality. The second term is the weighted sum of the inequality between the firms

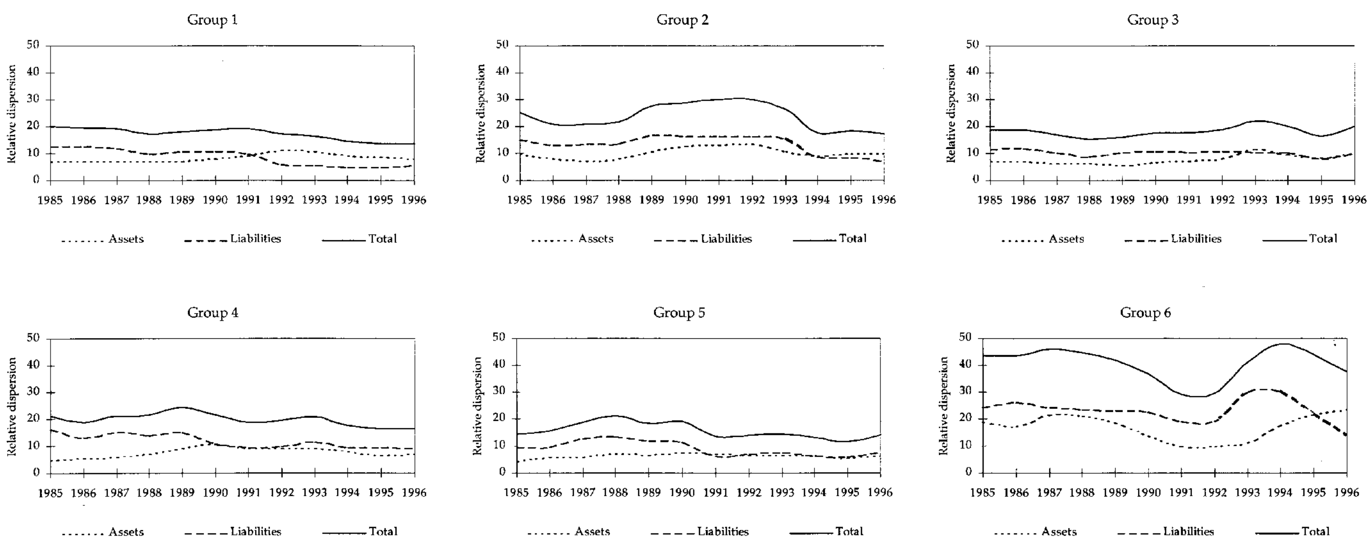

Fig. 4. *Convergence in specialization, total balance sheet* (*product mix groups*)

[18] Results were reported for six groups only, as one of them involves less than1% of total assets in the industry.

within each of the clusters. Thus, we are considering separately the inequality between clusters and within clusters for the item being analysed.

The results of the Theil index computations applied to the data show that, when bearing clusters formed on a year 1996 basis, the total inequality at every period is explained in an increasing percentage by the inequality between groups, revealing that the degree of the product line diversity is progressively being configured as a result of the different product bundles offered by the different clubs of firms (see Figs. 5 and 6).

This assessment holds for most of the analysed product lines (the nine balance sheet items). The two exceptions are other deposits and fixed-income securities, although the latter exhibits a steady growing inter group inequality (as a percentage of total inequality) since 1993. In fact, the tendencies are very clear for the 1993–1996 period; this could give additional robustness to the groups we are considering.

On the other hand, when 1985-product mix groups are considered, the pattern is just the opposite, as tendencies are reversed and there are no exceptions: intra group inequality involves a growing percentage of total inequality (see Figs 7 and 8), i.e. those groups of firms emphasizing similar lines of business in 1985, deeply influenced by firms' institutional nature, are being engaged to increasingly different activities.

VI. OPERATING COSTS, FINANCIAL COSTS, AND SPECIALIZATION

These tendencies observed up through the end of the 1980s and beginning of the 1990s bring new information to bear on the debate on banking firms' costs dispersion. In particular, one could delve more deeply into the reasons of such a dispersion, and make an attempt to ponder whether the increasing between groups inequality – when groups are chosen in 1996 – observed across different product lines is paralleled by a similar increase between groups' inequality in costs.

The approach to be followed in this section is rooted in the ideas by Kolari and Zardkoohi (1987, 1995): when concurrence forces are unrestrained, and firms' costs dispersion persists, reasons from this could come primarily from banking companies focusing on different activities. Thus, as some of these activities are more costly than others, some firms will be attached to the group of highest costs firms because of excelling in some lines of business requiring a more intense use of inputs.

Gual and Hernández (1991) assessed also the influence of Spanish banking firms' product mixes on operating costs, although following a widely different strategy, as they confined the analysis to year 1988, consequently not considering the possibility that specializations could have changed throughout time, and savings banks only. However, the

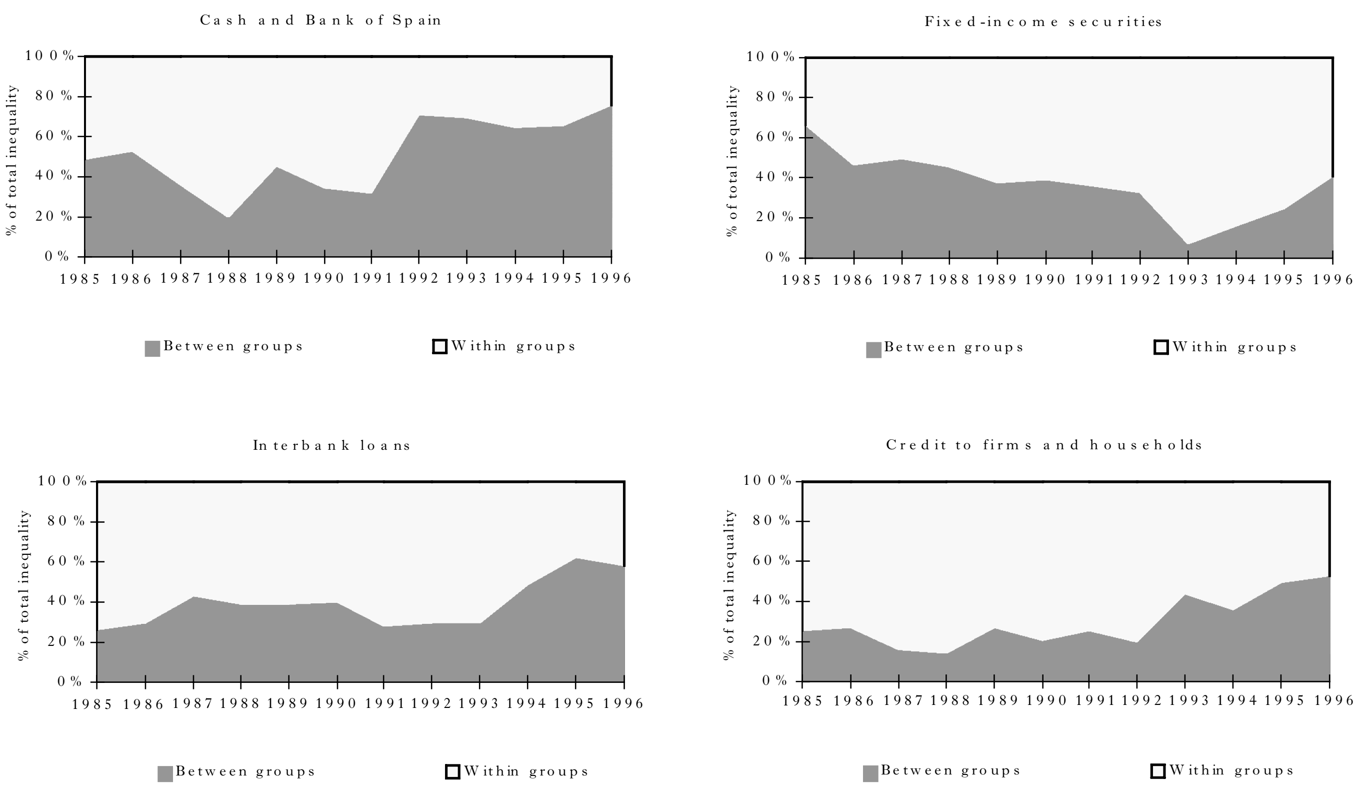

Fig. 5. *Evolution of inequality decomposition, assets (groups formed from 1996 data)*

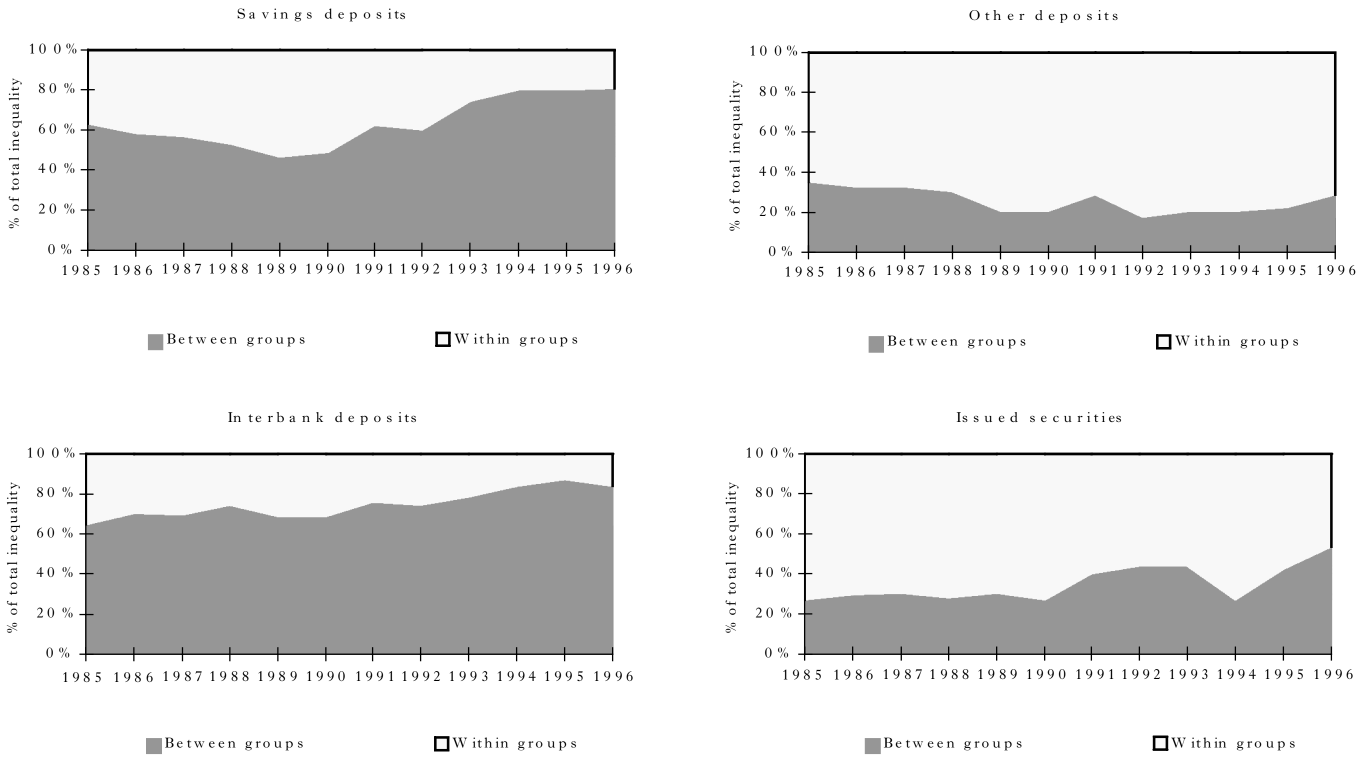

Fig. 6. *Evolution of inequality decomposition, liabilities* (*groups formed from 1996 data*)

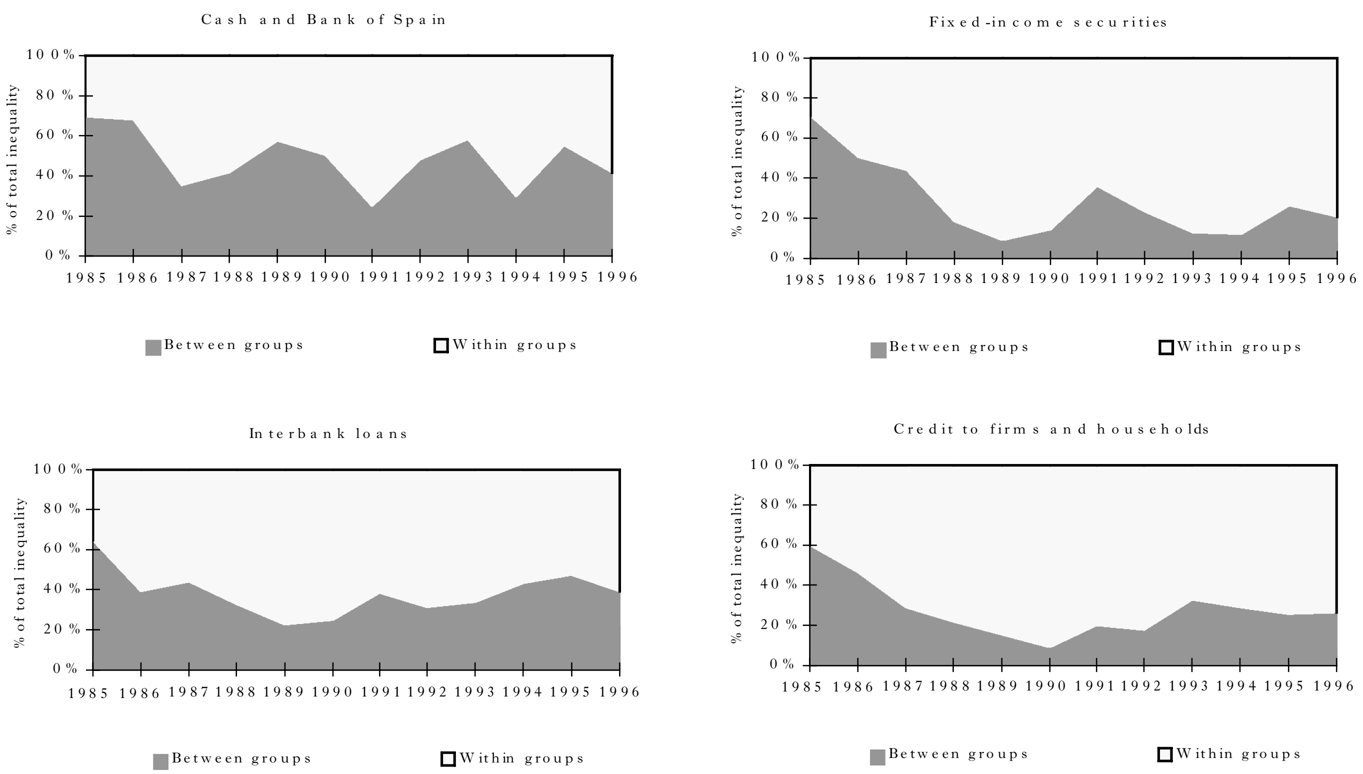

Fig. 7. *Evolution of inequality decomposition, assets* (*groups formed from 1985 data*)

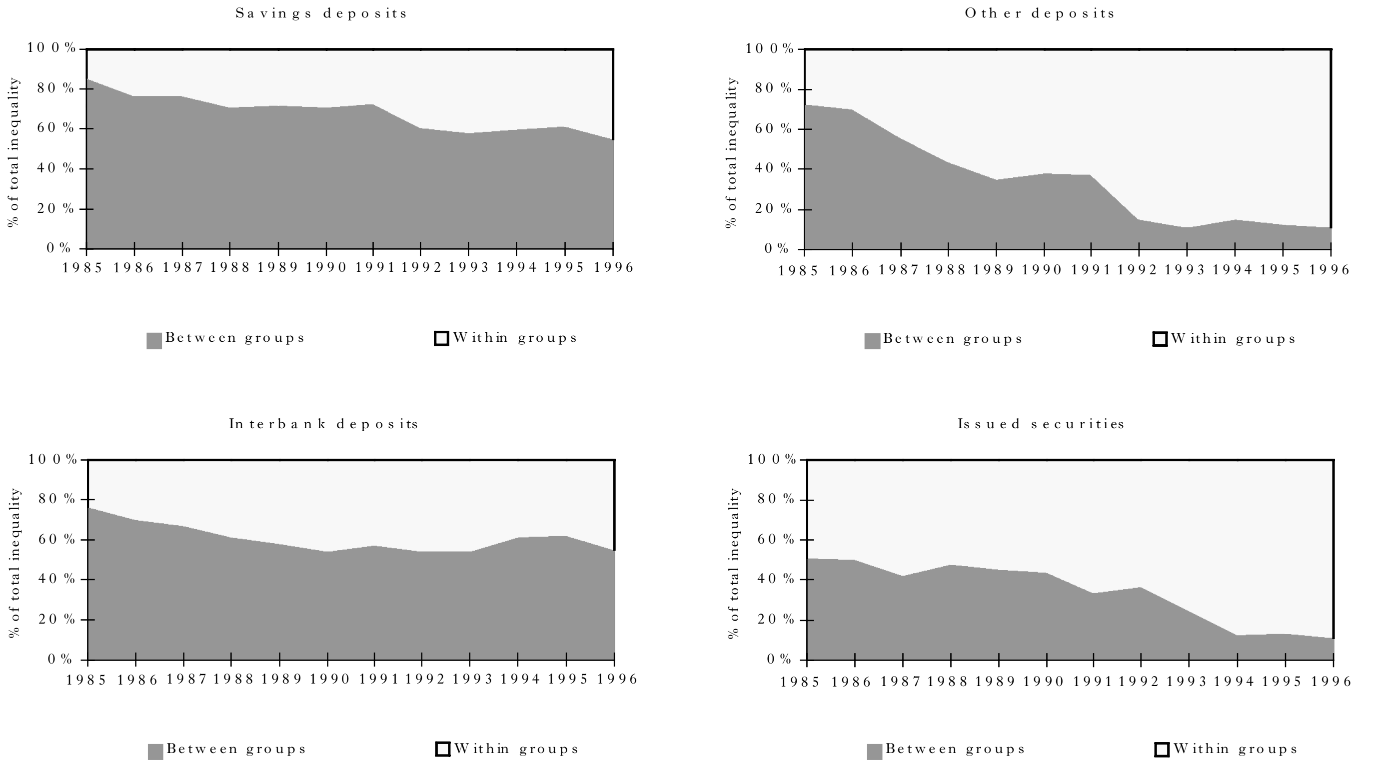

Fig. 8. *Evolution of inequality decomposition, liabilities* (*groups formed from 1985 data*)

conclusions were sound: when controlling for firms' specializations, (average) cost dispersion declines sharply.

Thus, in this section an analysis of the bias that specialization involves when analysing costs issues is to be considered. The approach is mainly descriptive, as we do not attempt to estimate the cost functions under which banks operate. It consists rather of falling back on the techniques applied throughout the paper. In particular, the Theil indexes might contribute to shed more light on this debate relative to the disparate average costs across firms, as they enable us to decompose both operating and financial costs inequality in between and within (product mix) groups inequality.

This new frame involves carrying out some changes into the analysis above and Equation 7. Such changes relate to subscript j in TI_j, as they now refer to either type of costs being considered, operating or financial, whereas formerly were linked to the item being analysed. The remaining terms of the analysis are unchanged. Thus, the first term on the right hand side of Equation 7 should be interpreted now as the contribution of the between (product mix) groups inequality to total operating or financial costs inequality, depending on the issue under study. The second term on the right should be interpreted as the contribution of the within (product mix) groups inequality, in either operating or financial costs.

The analysis has been accomplished for both groups in 1996 and 1985, as the increasing intra-group inequality found for the balance sheet items of groups made in 1985 could be also mirrored by a similar trend in costs.

Results are reported in Fig. 9. They show the percentage of total inequality generated by each type of inequality. The overall conclusion supports the prior beliefs as, indeed, and specially when operating costs are considered, cost inequality tends to fall sharply for those groups with increasingly similar output mixes, whereas the opposite pattern holds for those groups with similar balance sheet structures at the beginning of our sample period. Conclusions are similar for financial costs, although tendencies are more modest and with some bumps.

VII. FINAL REMARKS AND LINES FOR FURTHER RESEARCH

The developed analysis throughout prior sections has contributed to approach the study of the output mix evolution of banking companies and its tendency towards convergence or divergence. The techniques helped us in detecting some features of such evolution; in particular, it has been found that the higher freedom of banking companies in a less regulated and more

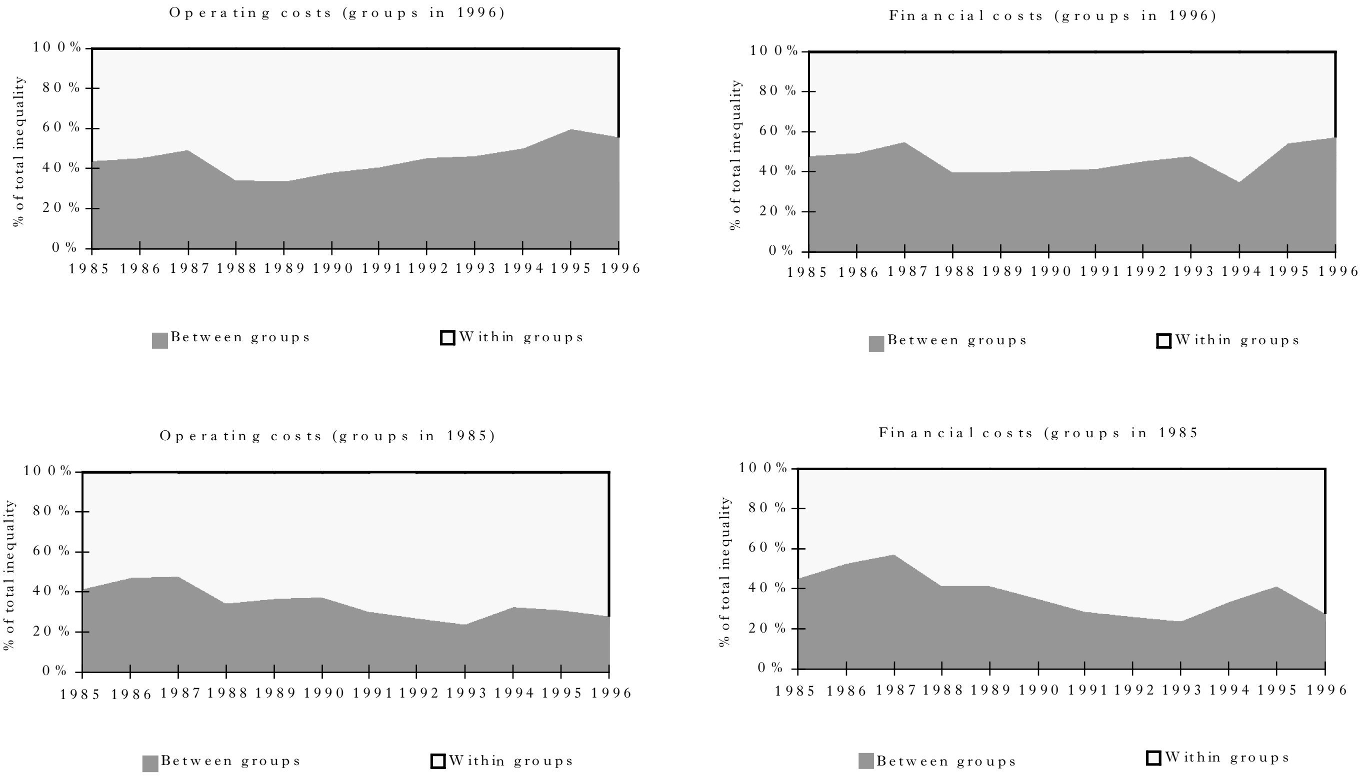

Fig. 9. *Evolution of inequality decomposition, costs*

competitive environment seems to produce a range of specializations or combinations of balance sheet items which makes banks more heterogeneous in their product mix.

However, it can also be appreciated that a special kind of similar firms in their specializations is being defined, and within each group we notice a fast and clear tendency towards increasingly more homogeneous product mixes. This explains much better the facts at hand. Although it can be argued that clusters' membership is rather unstable, and there could exist a bias towards convergence if groups are created in the final years, results show that banking institutions are experiencing strong changes in their product lines, regardless of their size or institutional nature. In addition, when product mix groups membership is identified at the beginning of the sample period (1985) tendencies are reversed and it takes place what one might hope, i.e. deregulation and increased concurrence affect markedly firms' product lines, as those firms initially engaged into similar activities end up with much dissimilar output mixes.

As a consequence of the results achieved both regarding 1996 output mixes, the heterogeneity of the specializations is increasingly higher between the different clusters but diminishes within them. If this tendency is to be confirmed, one might reasonably hope more similar product conditions within these clubs of firms competing against each others with similar product mixes.

Following such ideas, one has made a preliminary and somewhat descriptive approach, without estimating the coefficients of the costs functions under which bank companies might operate, in an attempt to delve into the links between specialization and costs. In particular, one assessed whether costs inequalities, both financial and operating, could be explained by product mix inequalities. The research answered this question positively, as intra (product mix) group inequality – in both types of costs – tends to fall steadily along the sample period.

Thus, the developed analysis on specialization should be thought of as a starting point for a more profound study of the differences in unit costs, scope economies, and efficiency. In particular, it should help in analysing if the different groups, as they produce different outputs, employ significantly distinct cost functions or have significantly different efficiency scores. In addition, during the last few years there have been developed some new techniques, broadly applied by the literature on economic growth and convergence, which could more precisely help us in detecting the dynamics of the variables of interest.

The optimal number of clusters and their membership stability over time

When no *a priori* segmentations of the industry into groups exist, the resort to statistical multivariate techniques turns out to be almost unavoidable, in order to consider unbiased groups. Most studies considering the segmentation of the industries into clusters of similar firms consider such techniques, and all of them face similar problems. In particular, and regardless of the considered variables and attempts pursued, two of them might be highlighted: the number of clusters and their stability over time.

Relative to the first issue, there is no unique and generally-accepted solution. Different studies consider methods which differ widely and, consequently, yield different results. Kolari and Zardkoohi (1987, 1995), for instance, specify a high number of groupings relative to the number of firms considered and reduce it until 'noticeable' differences between firms appear. Gual and Hernández (1991), with a sample of Spanish savings banks, argue that they are satisfactorily clustered into four groups, justifying this assertion by means of an analysis of variance. Fiegenbaum and Thomas (1990, 1993) stop clustering when comparing between groups variance (S_B) and total sample variance (S) show certain value ($R^2 = S_B/S \geqslant 65\%$) and adding an additional cluster increases fitness in less than 5% ($\Delta R^2 \leqslant 5\%$). Sánchez and Sastre (1995) try to lower the bias through the analysis of some statistics reported by the SAS software package used to form clusters. However, this statistics are not available for all clustering methods and for all software packages, and just by selecting a criterion involves a bias.

Unlike the problem of finding the optimal number of clusters, their stability over time issue is somewhat less technical, as the environment and its evolution influence clusters' membership markedly. This question turns out to be of paramount importance in a context of major changes, and makes it almost nonsense trying to find stable groups over time. In addition, there are not (again) commonly accepted rules to conclude a group is 'stable', and subjectivity is inherent to any of them. Amel and Rhoades (1988), for instance, argue that a cluster might be labelled as stable when, on average, roughly 60–70% of firms remain in the same group throughout the sample period.

The groups have been identified considering the above reasonings. The number of groups (seven) satisfies most of the mentioned criteria. In particular, such a grouping exhibits fairly good values for the statistics which may guide the decision,[19] according to the method followed (Ward). This result was achieved on a 1995 and 1996 basis, and it has much to do with the membership stability of clusters. Indeed, the final years of the sample were chosen because, on the one hand, we want precisely to assess if the groups of firms with similar output mixes that exist today were different at the beginning of the period and,[20] on the other, 1995 and 1996 constitute what Fiegenbaum and Thomas (1990) label as a Strategic Stable Time Period (STTP). Indeed, only the sub-periods 1993–1994 and 1995–1996 might be labelled as SSTPs. This reinforces the impossibility to find stable membership groups over time, and gives rise to the alternative exercise carried out above, i.e. if groups identified on a 1985 basis (and with the same criteria) exhibit the opposite patterns regarding output mix.

ACKNOWLEDGEMENTS

The authors are indebted to J. Maudos and J. M. Pastor for helpful comments and to the Instituto Valenciano de Investigaciones Económicas (IVIE) for kindly providing data and publishing a preliminary version of this article as a working paper (WP-Serie EC 98–02). Financial support from Fundación Caja Madrid, Fundació Caixa Castelló P1B98–21, Generalitat Valenciana GV90-135-2-08, and CICYT PB94-1523 is gratefully acknowledged.

REFERENCES

Amel, D. F. and Rhoades, S. A. (1988) Strategic groups in banking, *The Review of Economics and Statistics*, **70**, 685–9.

Barro, R. J. and Sala-i-Martin, X. (1992) Convergence, *Journal of Political Economy*, **100**(2), 223–51.

Berger, A. N. and Humphrey, D. B. (1992) Measurement and efficiency issues in commercial banking. In *Output Measurement in the Service Sectors* Z. Griliches (Ed), The University of Chicago Press, Chicago, pp. 245–87.

Dowrick, S. and Nguyen, D. T. (1989) OECD comparative economic growth 1950–85: catch-up and convergence, *American Economic Review*, **78**(5), 1010–30.

Fiegenbaum, A. Thomas, H. (1990) Strategic groups and performance; the U.S. insurance industry, 1970–84, *Strategic Management Journal*, **11**(3), 197–217.

Fiegenbaum, A. and Thomas, H. (1993) Industry and strategic group dynamics: competitive strategy in the insurance industry, 1970–1984, *Journal of Management Studies*, **30**(1), 69–105.

Freixas, X. (1996) *Los límites de la competencia en la banca española*, Fundación BBV, Bilbao.

Gual, J. and Hernández, A. (1991) Costes operativos, tamaño y especialización en las cajas de ahorro españolas, *Investigaciones Económicas*, **15**(3), 701–26.

[19] Such statistics are the cubic clustering criterion (CCC), the pseudo F, the pseudo t^2 and the R^2. See the SAS Institute (1990) for details.

[20] Despite this approach has the shortcoming, pointed out by Dowrick and Nguyen (1989), of being an *a posteriori* study of convergence. Thus, it could be argued that there could exist an *ex post* bias in favour of convergence as firms in each group show a similar product mix at the end of the analysed period.

Sala-i-Martin, X. (1996) Regional cohesion: evidence and theories of regional growth and convergence, *European Economic Review*, **40**, 1325–52.

Kolari, J. and Zardkoohi, A. (1987) *Bank Costs, Structure and Performance*, Lexington, Massachussets/Toronto.

Kolari, J. and Zardkoohi, A. (1995) Economies of scale and scope in commercial banks with different output mixes. Working paper, Texas A&M.

Mandos, J., Pastor, J. M. and Pérez, F. (2000) Competition and efficiency in Spanish banking sector: the importance of specialisation, *Applied Financial Economics*, forthcoming.

Pastor, J. M. and Pérez, F. (1998) Specialization and competitiveness of the Spanish savings banks: 1984–1995. In *Strategic Challenges in European Banking*, J. Falzon, and E. P. M. Gardener (eds), Macmillan, pp. 121–46.

Sánchez, J. M. and Sastre, M. T. (1995) ¿Es el tamaño un factor explicativo de las diferencias entre entidades bancarias? Documento de trabajo 9512, Banco de España, Servicio de estudios.

SAS Institute (1990) *SAS/STAT User's Guide, Volume I*, SAS Institute Inc., 4th ed.

Tortosa-Ausina, E. (1999a) Convergence in efficiency of the Spanish banking firms as distribution dynamics. Working paper, Series EC 99-14, IVIE.

Tortosa-Ausina, E. (1999b) *Especialización productiva, eficiencia y convergencia de las empresas bancarias españolas*. PhD thesis, Universitat Jaume I.